Using Precision Technology to Assess Forage Yield and Quality

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Abstract

Forage yield and quality are intrinsic factors that dairy producers must know to make informed management decisions. The determination of these factors prior to harvest can take various forms. In recent years, drone-based remote sensing technologies have emerged as powerful tools for gathering high-resolution data about forage growth and health. Among these technologies are photogrammetry, hyperspectral imaging, LIDAR, and multispectral imaging sensors. Photogrammetry uses high-resolution images captured by drones to construct detailed 3D models of forage, allowing for accurate estimation of forage height and biomass. Hyperspectral imaging captures data in hundreds of narrow spectral bands, providing detailed information on forage health and nutrient status. LIDAR technology uses laser pulses to measure the distance between the drone and the forage surface, allowing for precise height and biomass estimations. Multispectral imaging captures data in a few discrete bands, allowing for efficient analysis of forage quality and stress. From a data management and cost standpoint, photogrammetry may be the easiest for producer to implement.

Introduction

Alfalfa is one of the most important forage crops grown around the world and is widely used as a feed for livestock, due to its high protein content and digestibility. The yield and quality of alfalfa are critical factors that can have a significant impact on milk production and the profitability of the operation. High yields can ensure that producers maintain a consistent supply of feedstuffs throughout the year. The forage quality needs will depend upon the animal's nutritional requirement with lactating dairy cows requiring a higher quality plane of nutrition than 12 to 18 dairy heifers. However, from a forage production standpoint, yield and quality are inversely related and tradeoffs between the two must be considered. Yield will linearly increase over time, while the quality will decrease over time. Operations focusing on maximizing yield will reduce the nutritive and monetary value of the forage. Whereas, maximizing quality will increase the value of the forage but will decrease the overall production and impair stand persistence. Both yield and quality are influenced by plant maturity, harvest timing, season, pest pressure, weed control, disease pressure, soil fertility, stand density, water availability, and weather conditions. With regard to quality, approximately 70% of forage quality is determined by harvest timing.

Therefore, the general recommendation is to cut alfalfa every 28 days, as this harvesting frequency will provide an adequate quality and yield balance. The utilization of low lignin varieties of alfalfa has allowed for greater

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flexibility with cutting interval as harvest could be delayed by ~ 5 to 10 days. Nonetheless, a more desirable approach would be to base the harvest timing on the current crop conditions across the field. New technologies, such as unmanned aerial vehicles **(UAV)**, may allow for dairy producers to optimize both yield and quality to match their management goals.

Weather related challenges

The 28 days cutting interval has been recommended. However, the complicating factor in this region is related to the weather. In an evaluation looking at strictly rainfall events, the number of four-day harvest windows (day 1-cutting, day-3 raking/baling, and day 4- transport to storage) across Kentucky was found to average between 35 to 50 days across the entire season (May 1 to September 30; Figure 1). Thus, producers are encouraged to size the equipment and workforce for that time-period and forage harvesting goals. The evaluation of the four-day window over the past several years (2017 to 2021) has shown that we are generally seeing an increase in wetter weather when compared to the past 20 years. For May, the number of four-day harvest windows ranged between 0 to 18 days and averaged 6 days (Figure 2). Due to the limited harvest window created during this challenging harvest period in May, many producers have opted to wrap their 1st cutting as balage. It is theorized that the inclusion of other meteorological factors, such as soil moisture, cloud cover, temperature, and relative humidity, into the four-day harvest window evaluation would likely reduce the total number of four-day harvest window further.

University weather websites (https://weather.cfaes.osu.edu) provide a plethora of information to farmers. For instance, the UK Agriculture Weather Center Point Agriculture Forecast provides county level weather data. In addition to temperature, humidity, wind direction and speed, and growing degree days, other pertinent information is provided on a county level. The forecasted drying conditions (poor, fair, and good) and evapotranspiration rates are provided on a county level. Furthermore, the percent sky cover provides an indication of potential drying capabilities. Weather models have been developed that may streamline future alfalfa yield predictions. Weather data combined with information from forage variety trials across different states has shown that models using decision tree manifested a R2 of 0.982 for yield (Vance et al., 2022; Vance et al., 2023). Developed models for growth could be integrated into university weather websites.

Traditional measurement for yield

On most farms, yield had been traditionally measured on a field or farm level using bale counters and a scale system to estimate total production. The development of balers with scales and moisture meters has aided in the assessment of yield. Mass flow sensor have also been developed and used on large square balers (Kayad et al., 2015). Newer balers have added radio frequency identification **(RFID)** capabilities so that bales can be easily identified and tracked (AgCo, 2015; Drawdy and Weeda, 2022). The use of RFID has allowed for bales to be managed by field, stack, or truckload. Therefore, bales that possess a questionable moisture content could be easily separated from the rest. One of the new booths at the National Farm Machinery Show in Louisville this past year was the Ag Maximizer forage drier (Argi-Green, 2023) which can dry large square bales from 30% moisture to 15% in ~ 15 minutes. The drier system uses 78 spears to inject heat and air into the bales. From an Extension standpoint, studies analyzing the energetics and efficiency of this system need to be conducted so that recommendations could be made for large scale producers. From a yield standpoint, the location of bales within a field has also been characterized using drone imagery and image processing software (Seyyedhasani et al., 2021).

Assessing the alfalfa yield prior to baling has been estimated by measuring plant height and density. Unfortunately, this assessment strategy requires additional labor and time, and the samples acquired must be representative of the entire field. Additionally, simulation models (SIMED, ALSIM, ALFALFA 1.4, ALF2LP, and DSSAT-CROPGRO) have be utilized to predict yield but suffer from large data inputs.

Quality:

From a quality standpoint, bale sampling had been the traditional way to ascertain differences in nutritive value. Relative feed value has also been measured with baler sensors (Gaines). Bale moisture and relative feed value would be predicted and assigned specific bales.

Assessing alfalfa quality prior to baling within the field has typically relied on methods such as the predictive equation of alfalfa quality **(PEAQ)**. Nutritive values such as neutral detergent fiber **(NDF)**, acid detergent fiber **(ADF)**, and crude protein **(CP)** manifest predictive relationships with parameters such as height, maturity, weed pressure, and other factors. These relationships can be exploited by remote sensing technologies to aid in the rapid determination of forage parameters.

Available Technologies

Satellites, manned aircraft, ground-based platforms, and UAV have been equipped with various sensors to assess crop/forage yield and quality. According to the USDA survey from 2016-2019, approximately 7% of the corn and 10% the soybean acres have been analyzed with at least one of these technologies (McFadden et al., 2023). Of the available technologies, UAVs possess a multitude of advantages over other remote sensing systems (Table 1). UAVs provide the most cost-effective solution to collect high resolution spatial data. Furthermore, the easy of deployment allows for a high temporal resolution as well. The high resolution spatial and temporal data allows for site-specific management to take place on a field level. Monitoring and data acquisition can be conducted in real time. Furthermore, weather conditions can limit the use of manned aircraft or satellites, but UAVs can overcome this limitation.

UAVs

Three types of UAVs are available to researchers: fixed wing, multirotor, and hybrid. However, the multirotor UAV is generally preferred to as it is capable of vertical takeoff and landing, highly maneuverable, simple to operate, and cost effective to acquire. These capabilities provide the multirotor UAV with dynamic deployment and use capabilities. The hybrid UAV also has vertical takeoff and landing; however, this comes at a higher cost and maneuverability is sacrificed.

<u>UAV Flight Parameters</u>

With regard to UAV flight parameters, altitude, image overlap, and flight speed will influence the final detail and precision of images obtained. With the flight parameters, there are inherent trade-offs with efficiency related to flight time and processing time. For instance, increasing altitude will increase the area covered per flight and decrease the post-processing time and the spatial resolution (number of images per unit area). The increased area covered, fewer images, and faster processing times are all desirable. However, this reduced resolution may impair or skew decision making. The influence of overlap can be broken down into two parts: front and side overlap (Figure 3). Front overlap occurs in the direction of travel; while, side overlap occurs between the parallel flight paths. Overlap is required for the creation of orthomosaic images as tie points are essential to joining adjacent images. Increasing either overlap parameter will prolong flight time and reduce the area covered per flight. Increases in speed will generally increase the area covered. However, speed is limited by the sensors capability to achieve desired frame rate and spatial resolution.

Sensors

The sensor characteristics (resolution, focal length, angle, and acquisition rate) will also control the final detail and precision of the images or files collected. Table 2 lists the most common payloads utilized by UAVs, and there are tradeoffs with each sensor. For instance, hyperspectral will provide the most detail but will produce enormous data sets than can be cumbersome to analyze. For the hyperspectral, multispectral, and thermal cameras, the time of day for image acquisition is vital. The general recommendation for the time of day for UAV flight is noon. This will minimize shading and provide a more uniform reflectance. However for drought stress crops, the ideal time may be mid-morning after the dew has disappeared.

For the image and data acquired, the combination of the UAV flight parameters and sensors characteristics results in two very pertinent parameters: final model ground sampling distance **(GSD)** and root mean square error **(RMSE)**. GSD is the linear distance of each side of a pixel in the image and provides the models spatial resolution. RMSE specifies the difference between the actual and model directional components (X, Y, and, Z)

Visual sensors using photogrammetry

RGB (red-green-blue) cameras are equipped on most UAVs and provide the most cost-effective option for acquiring images for estimating forage yield and quality. Predefined flight paths (boustrophedonic pattern) allow for the systematic collection of RGB images based upon altitude, overlap, orientation, GPS coordinates, and other parameters. Photogrammetry utilizes the parameters from the overlapping photographs to create detailed 2D or 3D models of terrain, elevation, canopies, or crop surfaces.

In a 2017 Kentucky study that was performed throughout the growing season, twenty quadrats (1 m^3) were used to estimate yield and quality parameters in an 11 ha field (Dvorak et al., 2021). A Phantom 4 Pro with a 20-megapixel camera was used to record video [30 frames/sec, 4K ultra high definition **(UHD)**] at 10 m above ground level **(AGL)** and a flight radius of 5 to 10 m with the camera pointed at the quadrat. Images were extracted from the video and processed using Pix4D. Ground truthing was conducted within each quadrat as yield, NDF, ADF, and CP were measured. For yield, the R^2 value was found to be 0.63 when 2 variables (mean and standard deviation for UAV determined canopy height) were used to develop models for estimating yield. Similar for nutritive value, the R^2 values of 0.62, 0.63, and 0.62 were found for NDF, ADF, and CP, respectively. The inclusion of other variables, such as maturity, weed pressure, disease pressure, and insect pressure, increased the R^2 values to 0.81, 0.81, 0.78, and 0.79 for yield, ADF, NDF, and CP, respectively. However, the inclusion of the 4 other variables requires field evaluation by a technician which would require additional time and labor. In this trial, the maturity was largely consistent during measurement period and pest pressure was low.

For the 2019 alfalfa analysis, flights were conducted in a grid pattern at 30 and 50 m AGL with a Phantom 4 operating at 3.3 and 5.7 m/s, respectively (Minch et al., 2021). The front and side overlap were 85 and 75%. The gimbal was -90° (nadir) for each altitude with -75° being tested at 50 m AGL. Circular pattern flights at 10 m AGL and a flight radius of ~10 m was also conducted around 1 m quadrats. The work was initiated 7 days after the 1st harvest for the year and was conducted weekly until the next harvest after day 28.

As expected, the lower altitude grid pattern flights demonstrated the lowest GSD (0.77 vs 1.4 cm). With the lower altitude flights, gaps in the alfalfa canopy and wheel traffic from the ground sprayer are easily visible. In the yield estimation models, the inclusion of 2 variables (mean and standard deviation of UAV estimated height) demonstrated an R^2 of 0.60 for the circular pattern flights. The inclusion of a third variable (maturity) increased the circular pattern flights R^2 to 0.69. For the grid pattern flights, the inclusion of the third variable always increased the R^2 when compared to the 2 variable models. For the 2 variable yield models that possessed a camera angle of -90, the increase in altitude (30 to 50 m) resulted in a 16% increase in the R^2 value from 0.3. However, in the 3-variable model, the same camera angle and change in altitude resulted in a 19% decrease in the R^2 value from 0.68. Surprisingly, the best yield estimation with the lowest RMSE and highest R^2 was at 50 m AGL with a camera angle of 75°. The 2 and 3 variable models were shown to demonstrate an RMSE (kg/ha)/R^2 of 354/0.84 and 490/0.87, respectively. Although nutritive analysis was not conducted, similar results to prior work would be expected. This work was performed with different fields and varieties and would suggest that the model for yield would be resilient across a multitude of geographic locations.

LiDAR

LiDAR (Light Detection and Ranging) is a remote sensing technology that has revolutionized the way we collect data about the environment. By emitting laser pulses (ultraviolet, infrared, or visible light) and measuring the time it takes for the light to reflect back to the sensor, LiDAR can create detailed 3D maps of objects and landscapes. LiDAR has many applications in fields such as forestry, geology, archaeology, and meteorology and has gained popularity in agriculture for crop monitoring and yield estimation. One of the most important characteristics of LiDAR is its ability to measure distance with high accuracy and precision. This is achieved through the use of Time-of-Flight **(TOF)** technology, which measures the time it takes for the laser pulse to travel to the object and back to the sensor. LiDAR is an active remote sensing technique, meaning that it relies on its own energy source (the laser) to illuminate the target and measure the reflected signal. Another important aspect of LiDAR is the way in which it records and processes data. There are two main types of LiDAR data collection: full waveform and discrete. Full waveform LiDAR records the entire backscattered signal, which can provide a wealth of information about the target object or landscape. Discrete LiDAR, on the other hand, only records the first or last backscattered signal, which can be less accurate but is faster and requires less storage space. The choice between full waveform and discrete LiDAR depends on the specific application and the desired level of detail and accuracy.

Work to date with LiDAR and alfalfa has been limited to ground-based studies. In work that was conducted concurrently with the 2019 photogrammetry data collection, a low cost Scanse Sweep LiDAR sensor was used to acquire approximately 70 data points per quadrat

(Sheffield et al., 2021). This sensor emitted a single beam of light, and 3 to 4 revolutions of data were collected per quadrat. When the frame holding the LiDAR was attached to the quadrant, the final height of the LiDAR sensor was 2 m AGL. With regard to crop height determination, the LiDAR derived 95th percentile height descriptor was determined to be the optimum predictor of actual measure crop height with an R^2 of 0.90 and RMSE of 4.5 cm. The linear regression model for the 95th percentile developed provided the best fit for a single variable. Inclusion of other variables, such as other percentiles and pressures (insect, disease, and weed), only increased the R^2 by 0.02. The model also functioned better with thicker stand densities. For the yield assessments, the best model was determined to be a fine gaussian support vector machine **(SVM)** which provided an RMSE of 376 kg/ha and an R^2 of 0.75.

However, the LiDAR systems that are going to be equipped on most UAVs will likely possess multiple channels (collection of ~300,000 points per second) and will not be stationary. Increases in altitude or speed will decrease the point density which will reduce the spatial resolution. Point density is reduced as the speed increases.

Increases in speed allow for more acres to be flown per flight and reduces the computational requirements. Experiments in alfalfa that used a Velodyne Puck LITE LiDAR sensor on a linear motion test fixture showed that as the speed increased from 0.1 to 2.2 m/s, the maximum height measured (0.999 m) decreased by 13% (Dasika, 2018). Similarly, the number of points decreased from 300,000 to ~7,000 as velocity increased. The LiDAR sensor used in the study was 2 m AGL, and the point density would be much higher than would be typically expected in field measurement. The suggested maximum altitude and speed for the LiDAR sensor are less than 60 m AGL and 5 m/s. If the height estimation qualities are similar for soybean or corn, the optimum point density is 8 to 10 points/m³ and the minimum point density is 1 point/m³ (Luo et al., 2021). Nonetheless, high point densities may be required for short crops to have improved precision of height measurements. Penetration of the canopy by the LiDAR was also achieved, and the ground surface was detected. The difference between the LiDAR determined height and ground surface can be used to calculate the crop surface model. Penetration of the canopy may reduce the reliance upon UAV global navigation satellite system (**GNSS)** altitude measurement for accuracy. The difference between the height parameters measured and ground surface could be used to estimate height. Unfortunately, alfalfa measurement for height were confounded by lodging (Dasika, 2018). Thus, no R^2 or RSME was developed.

Hyperspectral

Hyperspectral imaging is a passive remote sensing technique that has become more ubiquitous in agriculture research due to its ability to capture images of an object or landscape in hundreds of narrow spectral bands, allowing for detailed analysis of the reflectance properties of different materials and surfaces. This technique has been widely used in agriculture for crop monitoring, yield estimation, and quality assessment. The spectral range captured by hyperspectral imaging in the visible **(VIS)** and near-infrared **(NIR)** regions of the electromagnetic spectrum is particularly useful for assessing plant health and nutrient status by detecting chlorophyll and other pigments associated with photosynthesis. By analyzing the reflectance spectra of forages in the VIS-NIR range, researchers can estimate forage yield, as well as identify areas of stress or disease.

In work conducted in Wisconsin in 2020, a DJI M-600 was flown with a Headwall Nano hyperspec push-broom scanner that measured 400 to 1000 nm with 274 bands (Feng et al., 2022). The flight altitude was 40 m AGL at 5 m/s to provide a GSD of 2.5 cm. Flights were conducted on the day of harvest, 1 week prior to harvest, and 2 weeks prior to harvest. Processing of the data was aided by the use of different machine learning tools: support vector regression **(SVR)**, random forest **(RF)**, artificial neural network **(ANN)**, and multitask learning **(MTL)**. In analyzing the nutritional aspects, the day of harvest and 1 week prior were shown to provide the best predictions for CP (R^2 =0.71 to 0.75) and ADF (R^2 = 0.53 to 0.60) with single-day data. The combined data set benefitted from the additional growth data provided by the time-series. The relationship among the three traits allowed for MLT to outperform the other models and demonstrate a R^2 of 0.84, 0.69, and 0.66 for CP, ADF, and aNDF, respectively.

One year prior (2019), yield estimations were conducted by the same group using equivalent flight parameters (Luwei Feng et al., 2020). Eighty published vegetative indices were evaluated and ranked using recursive feature elimination **(RFE)**. Machine learning models (RF, SVR, K-nearest neighbor **(KNN)** and ensemble) were used to predict the yield. Ensemble models, which combine the predictions from various base learners, were shown to significantly outperform RF, SVR, and KNN. For yield, the ensemble model demonstrated an R^2 of 0.874 and a RMSE of 220.8 kg/ha and outperformed the best performing single model **(KNN)** by 3 and 9% for R^2 and RSME, respectively. The selection of the top 25 VI, as opposed to the using the full features, allowed for the R^2 and RMSE to be improved for all the models. This study also showed the negative impact that compaction can have on yield; nonetheless, the yield estimations for the ensemble model demonstrated an R2 of 0.778 to 0.918 for the various compaction treatments.

In a ground-based hyperspectral analysis of alfalfa that was conducted in Minnesota, 400 to 2500 nm spectral data (visible **(VIS)**, near-infrared **(NIR)**, and short-wave infrared **(SWIR)**) was collected from 9 to 62 days after harvest (Noland et al., 2018). This hyperspectral measurement was augmented with the use of a single beam LiDAR, alfalfa maturity measurements, and the use of a modified growing degree units **(GDU)**. With the future intent to measure specific spectral band from a UAV, 21 nm bands were used to smooth spectral data, and regression (stepwise and random) was used to minimize the Bayesian information criterion **(BIC)** score and ultimately select the number of wavebands for each response variable (yield, CP, NDF, and aNDF). Six to seven wavebands were identified within the VIS-NIR range for each response variable. Across the response variable, 7 wavebands (351, 398, 461, 551, 667, 712, and 1077 nm) were determined to be common wavebands and were labels as "utility." VIS-NIR models resulted in a R^2 of 0.81, 0.78, 0.70 and 0.76 for yield, CP, NDF, and aNDF, respectively. The use of the utility wavebands resulted in an R^2 of 0.78, 0.73, 0.72, and 0.70 for yield, CP, NDF, and , respectively. The utility wavebands demonstrated similar prediction accuracy as the dedicated models. Nonetheless, the inclusion of an altered GDU allowed for the prediction accuracies of both VIS-NIR and utility wavebands to increase by ~20% for CP, NDF, and aNDF, yet the altered GDU resulted in only small increases in prediction accuracy for yield. The R^2 between LiDAR and yield was 0.85, and the yield equation is shown below. The inclusion of LiDAR in both VIS-NIR and utility wavebands allowed for the prediction accuracies of only yield to increase by approximately 6%.

Yield = 0.9474x+226.6

In a review of remote sensing in alfalfa, Tedesco et al. (2022) asserted that for yield and quality assessment, the following VIS-NIR wavelengths have demonstrated strong potential prediction accuracies: 428, 478, 529, 551,580,631, 670, 682,730, 733, 780, 783, 834, 865, 885, 933, and 983. Further work must be performed with these spectra to demonstrate viability across varieties, regions, and years.

Multispectral

Multispectral sensors capture images in several specific spectral bands, allowing for the detection and analysis of specific features or properties of crops and soil. The use of multispectral imaging in agriculture has facilitated various applications, including crop monitoring, yield estimation, and quality assessment. Multispectral imaging with drones typically utilizes a 5-band sensor that selects for blue, green, red, red edge, and infrared wavebands. In an 2018 experiment conducted at Washington State University (Chandel et al., 2021), a quadcopter was flown at 100 m AGL 2 to 6 day prior to the 1st and 3rd cutting of alfalfa, and the flight path for the quadcopter with a 5 band multispectral sensor was planned to achieve 85% front and 75% side overlap. Several VI were evaluated and multiple linear regression model was demonstrated to be the most desirable with an R^2 of 0.68. The limited number of day studies prior to harvest was surmised to limit potential of the models. The researcher suggested that adding weather data may strengthen future analysis.

Cost

From a producer adoption standpoint, the cost is a huge consideration. The per acre flight cost for conducting UAV flight with a RGB sensor and associated software are dependent upon the total number of flights conducted and associated average number of acres covered. If 52 flights were conducted over the growing season with 50 acres covered per flight (~15 minutes), the cost estimate would be ~$1 to 2 per acre per flight. With similar flight parameters, the multispectral sensor would possess a similar cost structure with ~$1.50 to 2 per acre per flight.

A larger drone would be required to carry the Lidar sensor or hyperspectral sensor. Hyperspectral sensors would be cost prohibitive for most farms. Therefore, the determination of specific waveband of importance would be essential for the development of dedicated lower cost sensors.

Availability

From a practicality standpoint, photogrammetry and multispectral analysis would be the easiest for producers to adopt. Farmers will undoubtedly face challenges, but the image analysis software allows for the processing to be conducted online. The use of the required equations would need to be simplified. Extension agents can help with the transition. Kentucky Agriculture and Natural Resource agents in two counties currently utilize UAVs with multispectral cameras to evaluate crops (including alfalfa). The drones were purchased by the individual counties. The cost for the image processing software was provided initially by the UK Barnhart Fund for Excellence Grant and is currently covered by the UK Biosystems and Agriculture Engineering Department.

Summary

Within agriculture, we are entering a more digital age, and adoption of new technology will be essential for the future viability of farms. Digital agriculture involves the integration of advanced technologies, such as sensors, drones, and artificial intelligence **(AI)** into farming practices. Real-time or near real time data collection and analysis will be the goal of future research endeavors. UAVs will allow for the rapid determination of yield and nutritive value of forages within a field or farm prior to harvest. It is important to note that UAV flights for commercial purposes (monitoring forages) requires producers to take and pass the FAA Part 107 knowledge test to become a licensed remote pilot. More research needs to be conducted with the "utility" waveband being used with a UAV platform. The inclusion of weather data, such as the modified GDU, seems promising for augmenting UAV collected data. Weather will ultimately still play a dominating role in determining when to cut. Nonetheless, the addition of UAV estimated yield and quality should allow for producers to better characterize their go/no-go decision-making strategies for harvest.

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Table 1. General comparison of common remote sensing technologies (Delavarpour et al., 2021).

Specification	Ground-Based	Satellite	Manned Aircraft	UAVs
Cost	Low	Highest	High	Lowest
Susceptibility to Weather	Yes	Yes	Yes	Limited
Feasibility for Small Fields	Yes	No	No	Yes
Spatial Resolution	Highest	Low	Moderate	Highest

Table 2. General summary of common UAV sensors (Delavarpour et al., 2021).

UAV Sensor	Cost	Description	Uses[1]
RGB (Red-Green-Blue) Camera	Low	Visual bands-Visible red, green, and blue information	1. Orthomosaic 2. Photogrammetry 3. DEM, DTM, CSM 4. Vegetative height 5. Inferred quality from height
Multispectral Camera	Moderate	Five-bandpass inference filter Blue (~475 nm), green (~560) nm, red (~668 nm), red edge (~717 nm) and near infrared (~840 nm)	Vegetative indices Detection of diseases and weeds
Hyperspectral Camera	Highest	100’s of bands	1. Plant stress 2. Compositional analysis 3. Quality assessment
LiDAR (Light detection and ranging)	Moderate	Rapid pulses of light	DEM, DTM, CSM, Crop height
Thermal	Moderate	Infrared radiation	Water stress

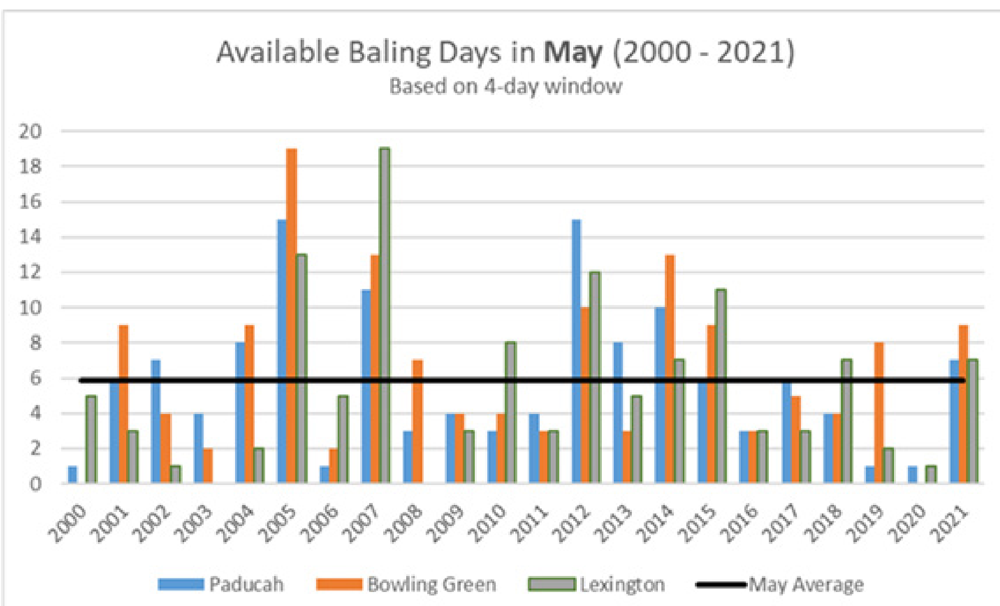
[1]DEM = Digital Elevation Model, DTM = Digital Terrain Model, and CSM = Crop Surface Model

Available Baling Days *						
Lexington						
	May	June	July	August	September	Annual
2000-2021 Avg	5.5	6.5	6.2	8.2	12.5	38.9
2017-2021 Avg	4.0	5.0	6.2	7.0	13.2	35.4
Deviation	-1.5	-1.5	0.0	-1.2	0.7	-3.5
Bowling Green						
	May	June	July	August	September	Annual
2000-2021 Avg	6.4	7.4	6.7	9.2	11.7	41.4
2017-2021 Avg	5.2	7.4	8.4	6.0	11.0	38.0
Deviation	-1.2	0.0	1.7	-3.2	-0.7	-3.4
Paducah						
	May	June	July	August	September	Annual
2000-2021 Avg	5.8	9.1	10.3	10.7	13.0	49.0
2017-2021 Avg	3.8	8.0	11.2	10.0	14.0	47.0
Deviation	-2.0	-1.1	0.9	-0.7	1.0	-2.0

* Based on 4-day window.

Data Courtesy: Midwestern Regional Climate Center cli-MATE toolkit: https://mrcc.purdue.edu/CLIMATE/

Figure 1. Available baling days (4-day window) in across the entire hay season in Kentucky from 2000 to 2021. Four-day window only considers rain events.



Data Courtesy: Midwestern Regional Climate Center,
cli-MATE Tools Environment, https://mrcc.illinois.edu/CLIMATE/

Figure 2. Available baling days (4-day window) in May across Kentucky from 2000 to 2021. Four-day window only considers rain events.

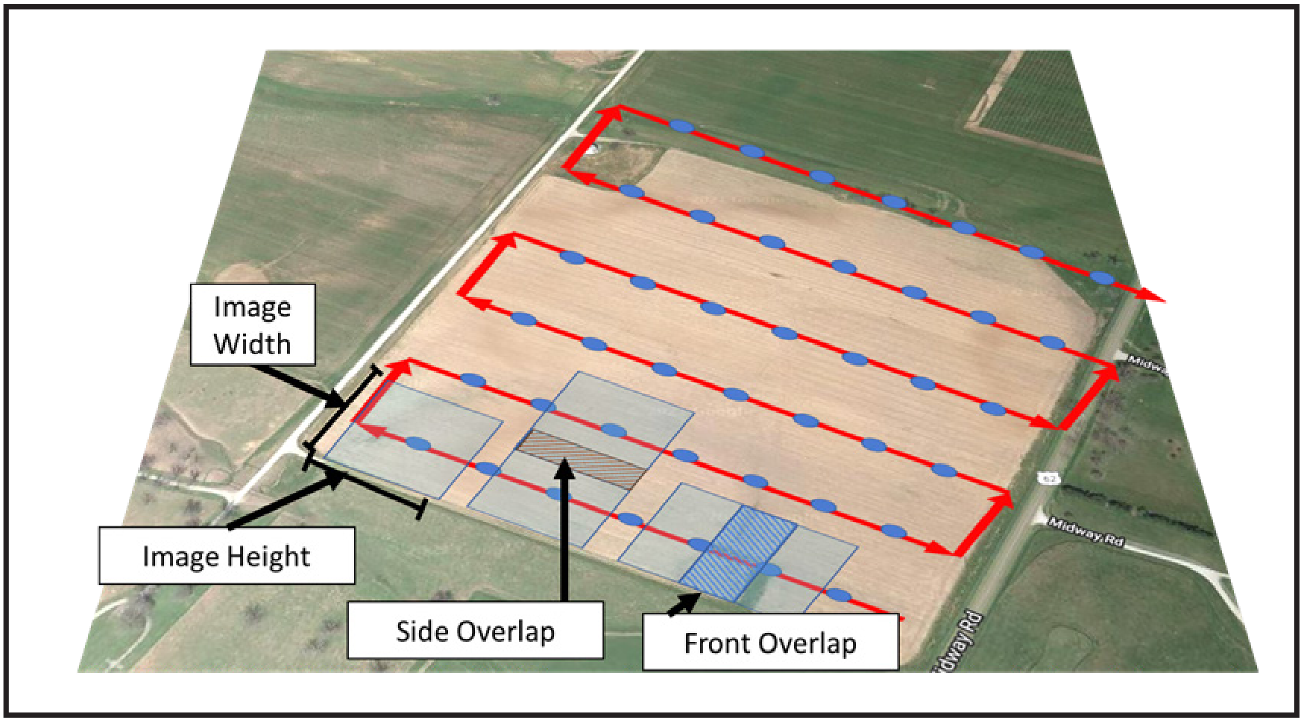


Figure 3. Front and side overlap along UAV flight paths.